WE CLAIM:

1. (canceled) rewritten/re-presented in claim 5

2. (canceled) rewritten/re-presented in claim 6

3. (canceled) rewritten/re-presented in claim 7

4. (canceled) rewritten/re-presented in claim 8

5. (canceled) rewritten/re-presented in claim 9

6. (canceled) rewritten/re-presented in claim 10

7. (canceled) rewritten/re-presented in claim 11

8. (canceled) rewritten/re-presented in claim 12

9. (re-presented - formerly independent claim 5) A method of recognizing an observed subsequence as being generated by one of a set of Hidden Markov Models (HMM), characterized by:

   - the fact that it searches the subsequence, Q, that offer the minimization of an inverse confidence measure, over all possible matchings,
   - where the inverse confidence measure is one of

     1) the accumulated posterior, normalized with the length of the matched subsequence X_b^e (aka. 'simple normalization')

$$\frac{-1}{e-b+1}\log P(Q|X_b^e)$$

2) partitioning the states in a HMM into phonems, having a function Phonemes(Q) that returns the segmentation of a path Q in the HMM into phonems, and computing one of:

2a) the worst average match in a phoneme, called 'real fitting',

$$\underset{Q}{\operatorname{argmin}}\left(\max_{\mathcal{Q}\in Phonemes(Q)} \frac{\sum_{q^k\in\mathcal{Q}} -\log P(q^k|x_k)}{|\{k|q^k\in\mathcal{Q}\}|}\right)$$

2b) double normalization of the accumulated posterior over the number of phonemes, J, and over the number of acoustic samples, $e_j - b_j + 1$, where e_j is the time frame where Q enters phoneme j, and b_j is the exit time frame from each phoneme, j,

$$\frac{-1}{J}\sum_{j=1}^{J}\left(\frac{1}{e_j - b_j + 1}\sum_{n=b_j}^{e_j}\log P(q_j^n|x_n)\right)$$

- and allows for the optional revaluation of the alternatives that offer the highest scores of a mentioned confidence measure on the basis of another confidence measure,

- and when based on the confidence measure called 'simple normalization' uses a method that applies Viterbi decoding for a HMM obtained by extending the initial one with a filler state just after start and one just before the termination state, and estimates the emission probability of the filler states in an iterative manner as being equal to the inverse confidence measure in the previous iteration,

and where the emission probability in the filler states in the first iteration can be initialized to any floating point number, but the iteration stops:

    i at convergence yielding the estimation of a keyword's boundaries and score as the obtained boundaries and score of non-filler states of the HMM,

    ii when the confidence measure descends under a threshold value, T, estimating only the keyword existence,

    iii when the emission probability of filler states, ε_0 is initialized with T and is reestimated, as value of ε_1 at the end of the first iteration, to be higher than T deciding keyword inexistence,

- or for any of the three confidence measures: 'simple normalization', 'double normalization' or 'real fitting', uses a beam-search-like algorithm that considers the emission probability of the filler state as zero, computes progressively for each pair of sample and state of HMM a set of possible alternatives paths to reach it, the computation of this set is based on the sets of paths that lead to the states that can be associated to the previous sample and extended with transitions allowed by the analyzed HMM,

  where this set can be reduced by using appropriate (safe) rules for the given confidence measure, ensuring the correctness of the inference,

  and where this set can be also reduced by using heuristics, for speeding up the computation despite the risk of reducing the theoretical quality of the recognition, heuristics of which a fast version stores only the best match,

and for all confidence measures one can prune the set of alternatives with safe rules guaranteeing optimality, where:

- the 'simple normalization' confidence measure with beam-search is used with a safe pruning that discards a path Q_1 given the existence of a path Q_2 whenever $S_2 < S_1$ and $L_1 < L2$, where S_1 and L_1 respectively S_2 and L_2 are the minus of the cumulated log of posteriors along the paths, and the lengths of the paths, for the paths Q_1 respectively Q_2, and which can be optimized by sorting competing paths based on their cost

- the 'double normalization' confidence measure on HMMs where no path skips any phoneme is used with a safe pruning that discards a path Q_1 given the existence of a path Q_2 whenever one of the following tests succeed:

  (a) $l_2 \geq l_1$, $A > 0$, $B \leq 0$ and $L_c^2 A + L_c B + C \geq 0$

  (b) $l_2 \geq l_1$, $A \geq 0$, $B \geq 0$ and $C \geq 0$

  (c) $l_2 \geq l_1$, $A \leq 0$, $C \geq 0$ and $L^2 A + LB + C \geq 0$

  (d) $l_2 \geq l_1$, $A = 0$, $B < 0$ and $LB + C \geq 0$

  where we denote by a_1, p_1, l_1, respectively by a_2, p_2 and l_2 the confidence measure for the previously visited phonemes, the posterior in the current phoneme and the length in the current phoneme for the path Q_1, respectively the path Q_2, and we also use the notations $A = a_1 - a_2$, $B = (a_1 - a_2)(l_1 + l_2) + p_1 - p_2$, C=$(a_1 - a_2)l_1 l_2 + p_1 l_2 - p_2 l_1$, $L = L_{max} - \max\{l_1, l_2\}$, $L_c = -B/2A$ and L_{max} is the maximum acceptable length for a phoneme,

- the 'double normalization' confidence measure on HMMs where some paths skip phonemes is used with a safe pruning that discards a path Q_1 given the existence of a path Q_2 whenever $l_2 \geq l_1$, $A \geq 0$, $p_1 \geq p_2$ respectively $F_2 \geq F_1$,

where F_1 respectively F_2 are the number of visited phonemes for paths Q_1 and Q_2,

- the 'real fitting' is used with the safe pruning: Q_2 is discarded in favor of another path Q_1 if the confidence measure of the Real Fitting for the previous phonemes is inferior (higher in value) for Q_2 compared with Q_1, and if $p_1 \leq p_2$ and $l_2 \leq l_1$, where p_1, l_1, respectively p_2, l_2 represent the minus of the logarithm of the cumulated posterior respectively the number of frames in the current phoneme for the path Q_1 respectively Q_2,
- and besides the previously mentioned safe pruning, heuristic prunings are also used for removing paths when $p > L_{max}P_{max}$ in any state or when $\frac{p}{l} > P_{max}$ at the output from a phoneme,

  where p and l are the values in the current phoneme for the minus of the logarithm of cumulated posterior and for the length of the path that is discarded.

10. (re-presented - formerly dependent claim 6) The method of claim 9, where the method is used to estimate the existence of keywords and their position in utterances, using Hidden Markov Models that model keywords.

11. (re-presented - formerly dependent claim 7) The method of claim 9, where the method is used to estimate the existence of biomolecular subsequences and their position in the chains of DNA using hidden Markov models to model the searched subsequences, and where these models can be obtained by trivial translation from generalized profiles.

12. (re-presented - formerly dependent claim 8) The method of claim 9, where it carries out

the estimation of the existence of objects and their position in images, characterized by the fact that

- it uses models of objects as subsequences represented by Hidden Markov Models,
- namely sections through views of objects are modeled by Hidden Markov Models,
- it uses emission probabilities based on a distance computed between colors, simple distances being yield by a Gaussian with median at the target color, or a normalized inverse of the Euclidean distance in the RGB space,
- wherein the Hidden Markov Models that model the objects can be structured of distinct regions, that play in the frame of the method the role of the phonemes in claim 9,
- and wherein the models of the objects can be modified in a dynamic manner during decoding with respect to the transition properties (existence and probability) on the basis of the so far accumulated information in the process.